Data Hawks Literature Review

Source	**Increase of Demand in Air Travel (The Problem)**	**Extending Timeframes (Existing Research)**	**Existing Models**	**Methodology**	**Accuracy of Models**
Kim, S., Park, E. Prediction of flight departure delays caused by weather conditions adopting data-driven approaches. J Big Data 11, 11 (2024). Source	The global air passenger transport market **doubles** every 15 years. A significant challenge in delivering satisfactory services to these increased passengers is the frequent occurrence of unexpected flight delays and cancellations. **Flight delays** have significant economic consequences for both airlines and passengers, rendering it a **notable issue within the aviation industry.** Here, we see the types and proportion of delays from 2010 to 2021 at JFK airport. We see that weather-related delays account for a small	**Existing research has predominantly concentrated on short-term** predictions, prompting this study to specifically address this aspect. This study aims to predict flight delays over more extended time frames (2 to 48 h) based on weather data. There is a pressing need for research that focuses on the **distant future using authentic long-term differential data.**	Here, we see a summary of prior flight delay detection research based on existing machine learning and neural network approaches. Previous Researchers have utilized Bayesian modeling, clustering, classification, and regression with diverse datasets from different regions.	The researchers used the following machine learning models and LSTM neural network to predict flight takeoff delays: **1. Decision Tree (DT)** **2. Random Forest (RF)** **3. Support Vector Machine (SVM)** **4. K-Nearest Neighbors (KNN)** **5. Logistic Regression (LR)** **6. Extreme Gradient Boosting (XGB)** **7. Long Short-Term Memory (LSTM)** To evaluate the performance of each classifier, the researchers calculated this confusion matrix and measured the accuracy, precision, recall, and F-score.	Tables 10 , 11, and 12 show the prediction results of flight departure delays based on weather data using various models. The results were obtained corresponding to a total of six different time differences (2, 4, 8, 16, 24, and 48 h). Furthermore, Tables 13, 14, and 15 provide an hourly breakdown of model accuracy from 1 h to 24 h, utilizing the same three datasets for ICN, JFK, and MDW airports, along with average training and testing times. The models achieved accuracy rates of 0.749 for ICN airport, 0.852 for JFK airport, and 0.785 for MDW airport in 2-h predictions. Furthermore, for 48-h predictions, our models

	proportion of delays (3.86%). However, **weather-related delays were longer than other types of delays,** with an average delay time of 69.81 min and a standard deviation of 100.79 min.	Hence, in this study, the researchers' objective is to specifically address and forecast flight delays of more than 2 hours.	Other previous researchers have used Bayesian modeling, decision tree, cluster classification, random forest, and hybrid methods.	**The researchers used the following datasets** to build their models: 1. Incheon International Airport weather (South Korea) 2. JFK Airport weather data 3. Chicago airport weather data 4. United states department of transport 5. Incheon Port Flight data	achieved accuracy rates of 0.748 for ICN airport, 0.846 for JFK airport, and 0.772 for MDW airport based on our experimental results. Based on the prediction results for the three regions, **the RF model demonstrated the highest performance for the ICN airport,** while the **LSTM model exhibited the highest performance for JFK and MDW airports**, with a minimum time difference of 2 h.

Source	Safety and Economic Consequences (The Problem)	The Goal	Data Collection	Analysis Methods
Meteorological Impacts on Commercial Aviation Delays and Cancellations in the Continental United States By: Christopher J. Goodman and Jennifer D. Small Griswold Source	In 2014, extreme weather events attributed 4.3% to the total number of delay minutes recorded by the Bureau of Transportation Statistics. **Weather was responsible for 32.6% of the total number of delay minutes recorded.** **Pilots** need to avoid weather that will negatively impact the safety of a flight and understand how it will impact the performance of the aircraft. **Air traffic controllers** need to understand where hazardous weather is, **Dispatchers** need to understand how the environmental temperatures will affect the takeoff and landing distances.	By better understanding the expected weather of an airport, planners and schedulers can create schedules that work to eliminate the impacts of expected weather predictions. The researchers work to identify the weather types and severity most related to flight cancellations and delays at selected airports with continuous weather records and high traffic for our period of interest (2003–15). With this knowledge, adjustments in the schedules can be made in areas where weather has created delays or cancellations in the past.	The analysis is completed on the 77 airports reporting data to the FAA, with a focus on 10 major U.S. airports with long weather records and high density flight traffic. While previous works have analyzed the impacts of weather on airline operations, these analyses covered past periods that may no longer be representative of current weather occurrences or aviation performance statistics or **covered only a short period** of time that is not representative of modern airline operations and concurrent weather patterns. According to researchers, these analyses provide the most up-to-date analysis of weather impacts on commercial airline schedules and aviation system performance. This work utilizes raw meteorological aviation routine weather reports (**METARs**) The **FAA** maintains a database	While predictive models aren't explicitly mentioned, the data processing and severity binning approach suggests that statistical analysis methods were used to derive relationships between weather conditions and delays. These methods likely form the foundation for future development of predictive models that could help anticipate delays based on forecasted weather conditions. The key takeaway is that weather severity and specific weather types (e.g., freezing precipitation, thunderstorms) were linked to flight delays and cancellations through statistical methods, which could be expanded into predictive modeling in future studies.

	Passengers need to know whether or not an upcoming weather event will cancel future flights. Weather impacts the economic performance of the aviation community by creating delays and cancellations. The economic costs of air traffic delays to the U.S. economy are vast. **In 2007, the total cost of airline delays was $41 billion dollars.** Weather plays a significant role in creating delays and cancellations and may cause up to 70% of the delays in the National Airspace System (NAS)		that contains information on the performance of the aviation industry and can be used to determine the impacts of specific weather types on the operational efficiency of the aviation community. The **ASPM** dataset contains performance and efficiency information for 77 U.S. airports and designated ASPM carriers. Here are the locations of the 77 airports.	

Source	The Problem	The Goal	Data and Methods	Previous Studies/Existing Models	Methodology	Results
Study of Delay Prediction in the US Airport Network by: Kerim Kiliç andJose M. Sallan Source	Flight delays carry severe social, environmental, and economic impacts. Dysfunctionality within air transport, such as flight delays, can cause **large economic losses.** A study from 2013 showed that a decrease of only 10% in flight delays could result in a $17.6 billion increase in the US net worth, and a decrease of 30% could result in a staggering $38.5 billion increase in US net worth. Flight delays also have a severe impact on the environment.	Researchers aim to use **Machine Learning** and **AI** to predict arrival flight delays in the United States airport network. The deployment of machine learning models predicting flight delays could lead to a significant improvement in air transport, along with economic benefits and a smaller environmental footprint. The aim of this study is to test different models that predict arrival flight delays in the United States airport network.	Data for this study comes from two public sets of domestic flight and weather data from 2017. Data are processed and split into training, validation, and testing data. The predictive model with the best performance is the **Gradient Boosting Machine**. We use flight data from the **Bureau of Transportation Statistics** and weather data from the **National Oceanic and Atmospheric Administration**. The most cited source of flight data is the **Bureau of Transportation Statistics** of the United States Department of Transportation.	Existing models use features related to weather are frequently used to predict delays. Other features used are seating capacity and automatic dependent surveillance-broadcast (ADS-B) data obtained from air surveillance systems. Most studies tackle delay prediction as a classification problem. The aim of these models is to determine if a flight is delayed or not.	Here is a helpful graphic on how they processed their data. Another helpful image of their data processing timeline. Here is how they split the training and testing data. This one includes validation. Each model will be tuned to find the optimal parameters. For each model, a confusion matrix will be constructed from predictions made on the unseen data in the testing dataset. Given this	Here they compare each model in a ROC Curve Here they compare each model with a PR AUC. **The gradient boosting machine model** outperformed others across all evaluation metrics. All models struggled with precision, likely due to the imbalanced nature of the dataset, where on-time flights greatly outnumber delayed ones.

			To have proper insight into model performance, in this study, a set of classification metrics will be evaluated to choose the best-performing model. These metrics will include, accuracy, recall, precision, F1 score, and ROC AUC.		matrix, they compute accuracy, misclassification, recall, precision, specificity, and F1 score. The next model metric they use is ROC curve The final metric they use is PR AUC	